Price Selection*

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Abstract

We propose a simple, model-free way to measure price selection and its impact on inflation. Price selection exists when prices that change at any given point in time are not representative of the overall population. Due to selection, upward movements in inflation tend to be driven by prices that adjust from below-average levels. Using detailed micro-level consumer price data for the United Kingdom, United States and Canada we find robust evidence of strong price selection across goods and services. Price selection accounts for around 39% of inflation variance in the United Kingdom, 26% in the United States, and 17% in Canada. Aggregation largely washes out price selection for regular price changes, but not for changes associated with price discounts. Price selection is stronger for categories where price changes are less frequent, larger in absolute magnitude, or in months with larger inflation deviations. This evidence favors multi-sector sticky price models with strong price selection at a sector level.

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1 Introduction

The extent to which prices respond to new information—to aggregate shocks, in particular—remains a fundamental question in macroeconomics. Slow adjustment at the microeconomic level lowers the sensitivity of aggregate inflation to economic slack, producing a flat Phillips curve. Such Phillips curves lie at the heart of the monetary transmission mechanism in most quantitative macroeconomic models that are used for policy analysis, and take center stage in characterizing the the monetary policy policy trade-off between inflation and output.[1]

The dominant approach to accounting for slow adjustment of individual prices builds on models of nominal price rigidity—usually referred to as "sticky price models." One of the big challenges in this literature, powerfully highlighted by Chari, Kehoe, and McGrattan (2000), is to reconcile microeconomic evidence of relatively frequent price changes with flat Phillips curves. Much of the literature has concentrated on exploring the mechanisms that could deliver flat Phillips curves despite ample price flexibility at a disaggregate level.[2] This literature, however, has largely abstracted from *price selection*—the mechanism that amplifies micro flexibility and therefore presents even more of a challenge for generating smooth inflation dynamics.

Selection exists when prices that change at a point in time are not representative of the overall population. Whether or not prices adjust depends on their gap with their desired level: prices with larger gaps would be more likely to adjust. Hence, in response to a common nominal shock the selection of prices with larger gaps may provide an additional impact on inflation.[3] For example, if prices that adjust in response to an unanticipated nominal expansion come from below-average levels, the associated individual price increases are larger on average, and the resulting inflation response is greater. Although the possibility of price selection is one of the prominent theoretical insights in this literature, there is hardly any evidence on whether it is empirically important.[4] The goal of this paper is to provide such evidence and explain its implications for sticky price models.

We propose a simple, model-free way of measuring price selection and its impact on inflation. We show how price inflation between periods $t-1$ and t can be identically represented as the product of the fraction of prices that change between period $t-1$ and t, and the difference between their average starting and ending levels, which we call *preset* and *reset* price levels. Namely, the preset (reset)

[1] We follow Golosov and Lucas (2007) and occasionally use the term Phillips curve to refer to a correlation between inflation and economic slack. Since we mainly focus on the dynamics conditional on monetary disturbances, we also associate flat Phillips curve with large real effects of monetary shocks.

[2] Notable examples are Christiano, Eichenbaum, and Evans (2005), and Smets and Wouters (2007). Nakamura and Steinsson (2013) provide a review of empirical evidence of these mechanisms.

[3] Studies of macroeconomic implications of price selection include Caplin and Spulber (1987), Danziger (1999), Caballero and Engel (2007), Golosov and Lucas (2007), Gertler and Leahy (2008), Nakamura and Steinsson (2010), Costain and Nakov (2011b, a, b), Midrigan (2011), Karadi and Reiff (2012), Head et al. (2012), Carvalho and Schwartzman (2015), Alvarez and Lippi (2014), Alvarez, Le Bihan, and Lippi (2016).

[4] There are only a few studies of the price pass-through of firm- or product-level shocks to marginal costs, and they provide a wide range of estimates: from none or very small (Carlsson, 2016) to virtually full pass-through (Eichenbaum, Jaimovich, and Rebelo, 2011). Gagnon, López-Salido, and Vincent (2012) study the effect of large inflationary shocks on the timing of price changes using Mexican CPI data: they provide evidence for the response of the timing of price changes to inflation shocks, but they do not identify how much of this response is due to price selection.

price level is the average period-$(t-1)$ (period-t) level of prices that change between periods $t-1$ and t relative to population average in period $t-1$. When selection is present, upward (downward) movements in inflation would be largely driven by prices that adjust from below-(above-)average levels, and so the preset price level would negatively correlate with inflation. In the absence of selection, the average starting level of adjusting prices would coincide with last period's population average, and so the preset price level would not vary. This definition can be easily applied to micro data for assessing the degree of price selection, and to simulated data generated by sticky price models to gauge plausibility of their predictions.

We employ three detailed micro price data sets to document price selection. For the United Kingdom, we use the data set underlying construction of the Consumer Prices Index (CPI) by the U.K. Office for National Statistics (ONS). The data set provides unit prices for goods and services that are included in the household final monetary consumption expenditure component of the U.K. National Accounts, representing about 57% of the U.K. CPI basket. Prices are collected locally for more than 1100 categories of goods and services a month, and more than 14,000 retail stores across the United Kingdom. The sample period includes 236 months, from February 1996 till September 2015. Likewise, for Canada we employ the Consumer Price Research Database (CPRD) compiled by Statistics Canada from price surveys used to construct the non-shelter portion of the Canadian CPI. The dataset contains information about prices posted by retail outlets across Canada during 143 months from February 1998 to December 2009, spanning more than 700 categories of goods and services representing about 61% of the consumption basket underlying the CPI. Finally, for the United States, Symphony IRI scanner dataset provides weekly expenditures and quantities for individual products across 31 product categories over 132 months from January 2001 to December 2011. The product categories cover food and personal care goods sold by grocery stores in 50 U.S. metropolitan areas.

First, we compute the average price change, the fraction of price changes, and reset and preset price levels for each month, product category, and sampling stratum (given by location and store type). Second, in accordance with price measurement methodologies in the United Kingdom, United States, and Canada, we combine these variables across strata to obtain category-specific indices for inflation, the fraction of price changes, and reset and preset price levels, where each stratum receives a weight that reflects its relative importance in households' consumption expenditures.[5] We summarize the extent of price selection by the share of the variance of the average size of price changes explained by the preset price level. This statistic, with a "minus" sign, is given by the coefficient in the regression of the preset price level on the average size of price changes—for brevity, we refer to this coefficient throughout as "price selection". By construction, zero price selection implies that changes in the reset price level do not contribute to inflation fluctuations. We test this hypothesis in the micro data.

For our benchmark case, we exclude price changes associated with price discounts and product substitutions, and we exclude calendar-month fixed effects. The weighted mean price selection

[5] See ILO (2004).

across product categories is –0.385 for the U.K., –0.259 for the U.S., and –0.172 for Canada, all statistically significant at 1% confidence level. These moments are little affected by including calendar-month fixed effects, or by adding category-specific linear trends. Including price changes associated with price discounts or substitutions does not materially influence price selection at a category level. Furthermore, to condition price selection on business cycle frequencies, we strip the regression variables of high and low frequencies by applying the Baxter-King bandpass filter. As a result, price selection remains statistically significant, although its magnitude is roughly half of the magnitude for monthly series: –0.231 for the U.K., –0.143 for the U.S., and –0.044 for Canada.

The degree of price selection weakens with aggregation of the data. Using evidence for food products in the U.K., we show that when we further disaggregate category-level reset and preset prices by geographical location and store type, price selection is stronger by about a third. By contrast, when we aggregate the variables to COICOP class level—a coarser classification of goods and services—price selection is weaker by about 42%. This evidence cannot be accounted for by standard one-sector sticky price models.

We then study the degree of price selection at the *aggregate* level. Category-level variables are combined using expenditure weights, and the regression of preset price level on the average size of price changes is applied to these aggregate variables. We find that for aggregate time series regular price selection is substantially weakened. For the benchmark case—no discounts, substitutions or seasonal effects—price selection is –0.198 for the U.K., and it is not significantly different from zero for the U.S. and Canada. Similar to the category-level evidence, including substitutions does not change price selection at the aggregate level. By contrast, including price discounts in the regression analysis, preserves a substantial degree of price selection in the U.K. (–0.394) and the U.S. (–0.140), which is close in magnitude to price selection at the category level. Hence, aggregation largely washes out price selection for regular price changes, but not for price discounts. This finding reflects a special nature of price discounts as an independent margin of price adjustment in response to aggregate shocks, and underscores their role for amplifying cyclical variation of the aggregate price level, recently emphasized for the U.K. and U.S. by Kryvtsov and Vincent (2017). In Canada, aggregate price selection is zero for either regular or all posted prices, consistent with less cyclicality in sales behaviour.

Price selection is the key mechanism that determines the inflation-output trade-off in business-cycle models. This has been demonstrated by Caplin and Spulber (1987), Danziger (1999) and Golosov and Lucas (2007) using menu-cost models, where selection arises because firms can choose to incur a menu cost to change their prices. Those price that adjust tend to be the most misaligned, and hence the associated price changes tend to be large. This increases the sensitivity of aggregate inflation to economic slack, for any given degree of microeconomic price stickiness. The degree of price selection, however, may be affected by idiosyncratic factors, such as product-level disturbances (Gertler and Leahy, 2008), economies of scale in price-adjustment technology (Midrigan, 2011), stochastic volatility of idiosyncratic shocks (Karadi and Reiff, 2012), the number of products per retailer (Alvarez and Lippi, 2014), the risk of pricing mistakes (Costain and Nakov, 2011b), the slope of the hazard rate of price adjustment and sector heterogeneity in price stickiness (Carvalho and Schwartzman, 2015). The most widely used Calvo (1983) sticky price model with random and exogenous timing of price adjustments represents an extreme case with zero price selection. Hence, sticky price models offer a wide range of predictions for the degree of price selection, and the associated size of real effects after monetary shocks.

We demonstrate this range by studying price selection in sticky price models. Namely, we calibrate three mainstream sticky price models to match standard price-setting moments from the micro data, and compute price selection for the micro data generated from these models. We entertain three canonical frameworks from the literature (Taylor 1980, Calvo 1983, and Golosov and Lucas 2007). Their parameters are chosen to match the same set of key pricing moments. We document that price selection varies substantially across models, accounting for nearly zero fraction of inflation variance in the Calvo model, 34% in Golosov-Lucas (GL) model, and 44% in Taylor model.

To identify and quantify the degree of price selection the literature has relied on indirect inference, whereby the model in question is matched to the key moments of the observed price behavior at the firm level. Despite relative success with broadly matching the micro data, the range of price selection predicted by calibrated sticky price models remains relatively wide. In principle, this failure of theoretical guidance is related to two unresolved issues. First, it is not clear which moments in the micro data pin down price selection and which are not—so matching models to several of the micro moments at a time does not necessarily provide accurate inference about price selection associated with those moments. Second, there are other mechanisms in sticky price models that jointly with price selection determine their empirical fit, most notably, real rigidities.[6]

The relationship between inflation and "reset price inflation" was studied in Bils, Klenow, and Malin (2012) (BKM). They define reset price inflation as the estimated rate of change of new prices set by the subset of price changers. Since the subset of price changers varies from month to month, the reset price inflation depends on both changes in the reset price levels and price selection. Using simulations of the Smets and Wouters (2007) business cycle model, BKM show that it is inconsistent with joint dynamics of inflation and reset price inflation in the U.S. data. Since price selection makes inflation more volatile and less persistent, our findings suggest that BKM's reset price inflation may be driven to a large extent by price selection. More generally, by offering a direct measure of price selection in the data, our paper helps to better calibrate the features of business cycle models that help them match inflation dynamics, such as price selection and the degree of real rigidities.

To provide additional testable implications for sticky price models, we study the relation between selected micro moments of price adjustment and the degree of price selection in the micro data. By exploiting rich variation in price adjustment across product categories, we document that price selection is stronger for categories where price changes are less frequent or larger in absolute magnitude. We also find support that price selection is stronger in months with larger inflation, thus

[6]Real rigidities, in the sense of Cooper and John (1988), Ball and Romer (1990), and Kimball (1995) arise when imperfections in goods or factor markets decrease the sensitivity of the individual firm's desired price level to economic conditions. As a result, the Phillips curve becomes flatter for any given degree of microeconomic price stickiness.

amplifying the effect of individual price changes on inflation, which is consistent with predictions of non-linear menu costs models. In all, our category-level evidence supports models with strong selection—menu cost and Taylor models, while Calvo model is more in line with weak-to-none aggregate regular price selection. Matching both aggregate- and sector-level price selection requires models with multiple sectors with state-dependent or Taylor price adjustment at the sector level.

Standard models have predominantly relied on Calvo nominal price adjustment and real rigidities to account for business cycles and the flat Phillips Curve. Our results suggest that a significant share of inflation volatility may be unaccounted for by these models, leading them to predict a flatter Phillips Curve. By construction, our measure of price selection is conditional on inflation, and therefore, we abstract from the shocks driving inflation dynamics or the mechanisms that relate inflation fluctuations to changes in real activity, such as real rigidities. We relegate it to future research to study these mechanisms and shocks jointly with price selection and draw implications for the inflation-output trade-off.

The paper proceeds as follows. We define and explain the concept of price selection in Section 2. Section 3 introduces the data sources and empirical definitions. We then identify and measure price selection in the U.K., U.S. and Canadian micro data in Section 4. Section 5 examines contribution of price selection in the battery of standard sticky price models. Section 6 concludes.

2 Definition of price selection

2.1 Basic intuition

The basic intuition behind price selection can be explained using Calvo and Golosov-Lucas (GL) models as examples. The two panels on Figure 1 provide a stylized representation of the probability of adjustment at a point of time for a log price, p, from a distribution of prices in the population. Let p^* denote a desired log price level at that point of time, common for all price setters. The dispersion of prices at that point of time is the outcome of infrequent price changes; otherwise, all prices would be equal to p^*. Two models considered here differ in the shape of the probability of adjustment function. In the Calvo model (Panel A), that probability for a given price follows an exogenous Poisson process with the arrival rate λ, and therefore the probability of adjustment is a flat function of p. In the GL model (Panel B), firms face fixed cost every time they adjust their prices. Since firm's profit function is concave with respect to the absolute distance between p and p^*, they are more likely to adjust their price the bigger that distance. Hence, the probability of adjustment is a convex function with respect to $|p - p^*|$, reaching the maximum of 1 when that distance becomes too big.

Now consider the change in the probability of adjustment in response to a common (aggregate or sector-specific) nominal shock: such a shock increases the desired level p^*, say, by 1%. Since the shock increases the distance $|p - p^*|$ for low prices and decreases it for high prices, it affects the probability of their adjustments. Graphically, this is captured by the shift of the probability function to the right by 1%. The distance between the pre-shock probability function (blue line) and after-shock function (red line) gives the change in the probability of adjustment for any price on the domain.

Since probability function is flat in the Calvo model, there is no change in how likely a given price p will adjust in response to the nominal shock. Hence, prices that adjust in response to that shock are representative of the whole population of adjusting prices. This is the example of no price selection. In the GL model, lower prices are more likely to adjust, and higher prices are less likely to change. Hence, in response to a positive nominal shock the average level of prices that adjust is lower than the average over population of all prices that change. This is the example of price selection.

Golosov and Lucas (2007) give an informal explanation of the selection effect along these lines. Caballero and Engel (2007) provide a formal treatment. They clarify that although probability of price adjustment monotonically increases with price gap $|p - p^{*}|$ in common sticky price models, the marginal contribution to the average price response after a monetary shock does not always monotonically increase with the price gap. Note that in our example the extensive margin complements price selection to amplify fluctuations of the average price level in response to common nominal shocks: both price increases (more frequent) and price decreases (less frequent) push the average price level up. Our definition below captures price selection regardless of whether or not it is correlated with extensive margin.

2.2 Inflation decomposition

Consider an economy with a continuum of goods, indexed by $i \in [0, 1]$, with $p_t(i)$ denoting log price of good i in period t. Let $G_t(p)$ denote the distribution of log prices in period t. The log of the aggregate price level in period t, P_t, can be defined as the mean of G:

$$P_t = \int_{-\infty}^{\infty} p \, dG_t(p) \ .$$

Inflation, therefore, can be fully characterized by the sequence of price distributions $\{G_t(p)\}$:

$$P_t - P_{t-1} = \int_{-\infty}^{\infty} p \, d\left[G_t(p) - G_{t-1}(p)\right] \ . \tag{1}$$

We can simplify this expression by focusing on prices that change from $t-1$ to t. Let $\Lambda_{t|t-1}(p)$ denote the measure of prices in the interval $[p, p + dp]$ in period $t-1$ that adjust between periods $t-1$ and t; and let $H_{t|t-1}(p' \,|\, p)$ denote their distribution in period t. The measure of prices in the interval $[p, p + dp]$ in period t is

$$\begin{aligned} G_t(p) \, dp = & \left(1 - \Lambda_{t|t-1}(p)\right) dG_{t-1}(p) \\ & + \left[\int_{-\infty}^{\infty} H_{t|t-1}(p \,|\, \widetilde{p}) \, \Lambda_{t|t-1}(\widetilde{p}) \, dG_{t-1}(\widetilde{p})\right] dp. \end{aligned} \tag{2}$$

The first term on the right-hand side is the measure of prices that were in the interval $[p, p + dp]$ in period $t-1$ and did not change. The second term is the measure of prices that did change to the level in the interval $[p, p + dp]$ in period t. To obtain this measure, first, for each price $\widetilde{p}$ in the domain, compute the measure of prices from an interval $[\widetilde{p}, \widetilde{p} + dp]$ in period $t-1$ that are adjusted to a point in the interval $[p, p + dp]$ in period t – it is given by $H_{t|t-1}(p\,|\,\widetilde{p})\,\Lambda_{t|t-1}(\widetilde{p})\,dG_{t-1}(\widetilde{p})$; second, sum across all prices $\widetilde{p}$. Using (2) to substitute for $G_t(p)\,dp$ in (1), yields

$$\begin{aligned} P_t - P_{t-1} = &-\int_{-\infty}^{\infty} p\,\Lambda_{t|t-1}(p)\,dG_{t-1}(p) \\ &+\int_{-\infty}^{\infty} p\left[\int_{-\infty}^{\infty} H_{t|t-1}(p\,|\,\widetilde{p})\,\Lambda_{t|t-1}(\widetilde{p})\,dG_{t-1}(\widetilde{p})\right]dp \end{aligned} \tag{3}$$

The first term on the right-hand side is (the negative of) the weighted mean of time-$(t-1)$ level of those log prices that change between periods $t-1$ and t, and the second term is their weighted mean time-t level, with both means weighted by the measure of adjusting prices. It is convenient to rewrite expression (3) in terms of price levels conditional on price adjustment. Let Fr_t denote the measure of price changes in period t, P_t^{pre} is the average time-$(t-1)$ level of log prices that adjust between periods $t-1$ and t ("preset price"), and P_t^{res} denote their average time-t level ("reset price"):

$$\begin{aligned} Fr_t &= \int_{-\infty}^{\infty} \Lambda_{t|t-1}(p)\,dG_{t-1}(p)\,, \\ P_t^{pre} &= Fr_t^{-1}\int_{-\infty}^{\infty} p\,\Lambda_{t|t-1}(p)\,dG_{t-1}(p)\,, \\ P_t^{res} &= Fr_t^{-1}\int_{-\infty}^{\infty} p\left[\int_{-\infty}^{\infty} H_{t|t-1}(p\,|\,\widetilde{p})\,\Lambda_{t|t-1}(\widetilde{p})\,dG_{t-1}(\widetilde{p})\right]dp. \end{aligned}$$

Then inflation decomposition (3) can be written as

$$P_t - P_{t-1} = Fr_t\,\left(P_t^{res} - P_t^{pre}\right). \tag{4}$$

Price selection then is identified by movements in P_t^{pre}, the average level of adjusting prices relative to the average level of all prices, P_{t-1}. Co-movement of $P_t^{pre} - P_{t-1}$ with inflation captures the workings of price selection as summarized earlier in this Section.

2.3 Comparisons to alternative inflation decompositions

Decomposition (4) provides a novel spin on decomposition in Klenow and Kryvtsov (2008), who cast inflation as the product of the average fraction of price changes and their average size conditional on adjustment. Our decomposition represents the average size of price changes, DP_t, as the difference between the average price level of newly set prices and their average level prior to adjustment,

$DP_t \equiv P_t^{res} - P_t^{pre}$.[7]

The relationship between inflation and "reset price inflation" was studied in Bils, Klenow, and Malin (2012). They define reset price inflation as the estimated rate of change of new prices set by the subset of price changers. Since the subset of price changers varies from month to month, the reset price inflation depends on both changes in the reset price levels and price selection. Therefore, their approach does not allow to identify price selection and quantify its impact on inflation dynamics.[8]

In a related approach, Caballero and Engel (2007), and Costain and Nakov (2011a) propose decomposition of inflation response to a monetary shock. This response is due to the cumulative impact of desired log price adjustments (price gaps), $p - p^*$, and can be decomposed into the contributions from changes in the size of adjustments by those prices that are adjusting regardless of the shock (the intensive margin) and from the changes in the fraction of price increases and decreases caused by the shock (the extensive margin). These definitions must rely on model assumptions about the process for the desired price level, p^*, and the conditional probability of adjustment as a function of the price gap, $p - p^*$. While this approach is well suited for demonstrating theoretical implications of price selection, it is not suitable for empirical assessment of price selection because the desired price level is not observed and is hard to measure in the micro data.[9] Caballero and Engel (2007) argue that in theory price selection is neither necessarily nor sufficient to increase the response of inflation to a nominal shock and propose instead focusing on the extensive margin. They clarify, however, that the extensive margin combines selection of price adjustments with their respective impacts on the average price response to a common nominal shock.[10]

In contrast to these approaches, our method is "model-free" requiring only information about price adjustments at the micro level, and it does not mix in the other adjustment margins, such as reset price changes. Decomposition (4) focuses solely on selection of prices that adjust from month to month—summing log price *levels* for those prices that adjust: the average starting and ending price levels of adjusting prices are what we call preset and reset price levels. We show that their difference, multiplied by the fraction of price adjustments is identically equal to inflation. The contribution of movements in the preset price level relative to population average, $P_t^{pre} - P_{t-1}$, to inflation dynamics then identifies price selection.

While our method does not rely on the desired price level or identified monetary shock, like

[7] Klenow and Kryvtsov (2008) and Nakamura and Steinsson (2008) decompose the variance of DP_t into terms due to price increases and decreases. Using U.S. CPI micro data they find that price increases play an important role in inflation fluctuations, while the role of price decreases may depend on the definitions of the time series and other controls.

[8] Using simulations of the Smets and Wouters (2007) business cycle model, Bils, Klenow, and Malin (2012) show that it is inconsistent with joint dynamics of inflation and reset price inflation in the U.S. data. Kara (2015) shows that this issue is less severe if business cycle models incorporate different degree of price flexibility across consumption sectors.

[9] Carlsson (2016) uses the producer price and cost micro data from Sweden to estimate firm-specific marginal cost changes (and therefore p^*); he finds a weak response of the timing of individual price changes to firms' marginal costs. In contrast, Eichenbaum, Jaimovich, and Rebelo (2011) find an almost perfect passthrough of cost to prices using scanner data for retail prices.

[10] Gagnon, López-Salido, and Vincent (2012) provide evidence of the quantitative importance of the extensive margin using Mexican CPI data in response to large nominal shocks—peso devaluation in 1994 and VAT hikes in 1994 and 2010.

in Caballero and Engel (2007) or Costain and Nakov (2011a), we show that it provides plausible measurement of price selection in a variety of sticky price models. In Supplementary Material (Section C), we theoretically derive contribution of price selection to inflation variance in plain-vanilla sticky-price models. In line with well-known results, price selection is zero in Calvo (1983) model, and it is infinitely large in Caplin and Spulber (1987). Head et al. (2012) (HLMW) study a model in which price dispersion arises due to decentralized trade and search frictions in the goods market. Their model nests Caplin-Spulber's "elevator-shift" mechanism as a special case; we show that with the benchmark parameter values, price selection in HLMW model accounts for almost one third of inflation variance. In Taylor (1980) model price selection accounts for the fraction $\frac{T-1}{2T}$ of inflation variance, where T is the duration of price contracts.[11]

In Section (5) we focus on versions of three most-commonly used sticky price models with both common and product-specific shocks: Taylor (1980), Calvo (1983), and Golosov and Lucas (2007). Model parameters are chosen so that all models fit the same set of moments of micro-price behaviour. Since all variables in (4) can be measured directly in the micro data, our approach allows us to apply decomposition (4) in the same way to micro data and artificial price data generated by the models. We show in Section (5) that price selection varies substantially across different sticky price models; we then draw takeaways from comparing price selection in sticky price models to price selection we find in the data.

3 U.K., U.S. and Canadian micro data

To measure the relationship between inflation and reset and preset price levels we need data on price changes at the level of individual goods and services. We employ three datasets for the United Kingdom, United States, and Canada. The datasets from the U.K. Office for National Statistics (ONS) and Statistics Canada provide prices for goods and services collected monthly from retail outlets used for the construction of the Consumer Prices Index (CPI) in these countries. The Symphony IRI dataset provides weekly scanner transactions data for grocery stores in the United States. Unlike ONS and Statistics Canada datasets that provide prices posted by retailers, the IRI dataset provides transaction prices. To the extent possible, our treatments of these datasets make the statistics comparable. The U.K. dataset has a broader coverage than the IRI dataset, and it is also available online unlike the Canadian dataset for which we have confidential access. We therefore rely extensively on the U.K. dataset for the multitude of our robustness checks. We also describe it in more detail below. The union of the three datasets provide rich coverage of micro price adjustment in three developed countries, and serve as an excellent source of evidence of price selection, see Table (1).

[11] Carvalho and Schwartzman (2015) show that Taylor sticky price model has the strongest price selection among models with time-dependent price setting.

3.1 U.K. CPI micro data

The dataset is compiled from the survey of prices for goods and services that are included in the household final monetary consumption expenditure component of the U.K. National Accounts. The survey includes prices for more than 1100 individual goods and services a month, collected across more than 14,000 retail stores across the United Kingdom. The survey excludes housing portion of consumer prices, such as mortgage interest payments, house depreciation, insurance and other house purchase fees. Also expenditures for purposes other than final consumption are excluded, e.g., those for capital and financial transactions, direct taxes, cash gifts. The portion of the data published on ONS website includes only locally collected prices, covering about 57% of the U.K. CPI basket.

Most prices are collected monthly, except for some services in household and leisure groups, and seasonal items. The sample period includes 236 months, from February 1996 till September 2015. The total number of observations is over 24 million, or about 100,000 per month.[12] Prices are collected across 12 geographical regions, e.g., London, Wales, East Midlands. There are four levels of sampling for local price collection: locations, outlets within location, product categories, and individual product varieties. For each geographical region locations and outlets based on a probability-proportional-to-size systematic sampling with a size measures based on the number of employees in the retail sector (locations) and the net retail floor space (outlets). The dataset contains prices collected locally in around 150 locations with an average of more than 90 outlets per location.

Product or service categories—or "representative items"—are selected based on a number of factors, including expenditure size and product diversity, variability of price movements, availability for purchase throughout the year (except for certain goods that are seasonal). There are currently over 1100 categories in the basket. Examples of categories include: Onions, Edam, Envelopes, Men's Suit (ready made), Electric Heater, Single Bed. Finally, for each category-outlet-location, individual products and varieties are chosen by price collectors based on their shelf size and regular stock replenishment.

For each category, ONS stratifies the sample by "strata," given by region and shop type pairing. For each category and stratum, ONS dataset provides sampling weights that reflect that category-stratum's relative importance in households' consumption expenditures. For constructing the CPI, ONS first construct elementary price indices for each product category-stratum bin by taking geometric means of all prices within the bin, with equal weights. These elementary indices are then aggregated into the CPI using consumption expenditure weights.[13]

[12] Detailed description of the CPI data sampling and collection can be found in the ONS (2014) and Clews, Sanderson, and Ralph (2014). The price quote data are available via ONS website: http://www.ons.gov.uk/ons/datasets-and-tables/index.html. Recent related work and additional details on data cleaning can be found in Kryvtsov and Vincent (2017), and Chu et al. (2015).

[13] Categories in the CPI are classified into 71 classes, according to the international classification of household expenditure, Classification of Individual Consumption by Purpose (COICOP). A CPI "class" represents a basic group category, such as "Meat", "Liquid Fuels" or "New Cars". Category and class weights a calculated based on the Household Final Monetary Consumption Expenditure (HFMCE) and ONS Living Cost and Food Survey

Throughout the paper, we provide two alternative treatments of price changes at individual product level. First, we distinguish price changes associated with temporary price discounts ("sales"). While sales are relatively infrequent—4.6% per month in the U.K.—they usually come with much larger and shorter-lived price swings than regular prices. We adopt ONS' definition of sale prices as temporary reductions on goods that are likely to be available again at regular prices or as end-of-season reductions. When posted price is discounted, the unobserved regular price equals to the posted price in the month preceding the first month of the sale; and it is equal to the posted price if there is no sale. These definitions are reliable for describing sales behaviour and are commonly used in the literature.[14]

Second, we differentiate price changes associated with product substitutions. When previously collected price-product is no longer available to a field agent, they make a substitution for another product from the same category. Such substitutions—5.6% per month in the U.K.—are more commonly associated with price increases (68% of price changes during substitutions).[15] Symphony IRI data contain prices for uniquely-defined products, and therefore we do not apply this treatment to these data.

3.2 Statistics Canada CPI data

Consumer Price Research Database (CPRD) compiled by Statistics Canada from price surveys used to construct the non-shelter portion of the Canadian CPI. The dataset contains information about prices for goods and services posted by retail outlets across Canada from February 1998 to December 2009, or 143 months. Overall, the CPRD contains more than 8.4 million observations (almost 60,000 per month) and covers about 61% of the consumption basket underlying the CPI. Since the CPRD is a dataset of individual prices, it excludes goods for which prices are aggregated indexes, such as utility rates, insurance premiums, transportation fares, sport and theater tickets, books and newspapers, entertainment CDs and DVDs, and computer equipment.

Similar to ONS, Statistics Canada defines a product category (representative item)—a single commodity, such as potatoes, yogurt, gas barbecue, women's gloves, oil filter, selected to represent a basic class of goods and services in the index. There are 705 specific product categories in the dataset. The selection of these items takes into account the following criteria: the price movement of the item should represent the price movement of the given class, the item has to be available on the market for a reasonable length of time.

Prices are collected from a variety of retail outlets, including supermarkets, specialty shops, department stores, garages, dental offices, and salons. In most cases, the main determining factor in

(LCF). Changes in the expenditure weights over time reflect changes in the expenditure composition of households' consumption baskets. Using class, category, stratum and shop type weights, we follow ONS methodology to construct observation-specific weights for our sample.

[14] Nakamura and Steinsson (2008) demonstrate that sales affect the measurement of the extent of nominal price stickiness in the U.S. CPI data. Kryvtsov and Vincent (2017) provide evidence of the countercyclical variation in the number of sales in the U.K. and U.S.; they also discuss different definitions of sales in the data.

[15] Klenow and Malin (2010) provide and overview of the incidence of sales and substitutions and their implications for price adjustment. Bils (2009) and Kryvtsov (2016) document the occurrence of price substitutions and assess the extent of the associated quality bias in the U.S. and Canadian CPI data, respectively.

the selection of outlets is the value of sales revenues for the items being priced. However, geographic dispersion and outlet type are also important factors to be considered. Pricing information is collected in up to 92 urban centres across Canada, generally in urban centres with a population of 30,000 or more.

Like the U.K. dataset, the Canadian dataset provides flags for the months corresponding to a sale (9.0% of monthly observations) or a product substitutions (3.5%). We therefore treat those observations in the same way as we do for the U.K. dataset.

3.3 Symphony IRI Inc. data for the U.S.

Symphony IRI is a marketing and market research dataset that contains scanner data, product description data, store data and household data.[16] The scanner data are provided at a weekly frequency for a panel of 31 grocery products, such beer, coffee, milk, razors, laundry detergents, frozen pizza. To make IRI data set comparable to the CPI data sets, we convert weekly observations into monthly by using the first available weekly observations from that month. In all, the dataset contains around 1.5 billion observations, or 36.2 million monthly observations, covering the span of 132 months, from January 2001 to December 2011, or around 274 thousand per month.

The data are provided for grocery stores in 50 U.S. metropolitan areas. Each store has a unique identifier, so its prices and quantities can be tracked over time. Scanner data include the revenue and quantity for weekly purchases for each product, identification for the product, display indicator and sale indicator. For each individual product in a product category, we define a unique product identifier by matching UPC codes for that product with product description (e.g., Budweiser lager 355ml). We only include stores belonging to chains that exist throughout the entire sample period. We exclude products that belong to a store's private label (their coding was changed by IRI in 2007 and 2008), and products which have less than two observations per week; and we exclude observations with a unit price less than $0.10.

Similar to strata in the ONS and Statistics Canada data, we define an elementary bin in IRI data to be represented by a category and metropolitan location. The share of nominal revenues over the sample period in total revenues over the sample period is used as a stratum weight. In a given week, unit prices for each UPC are constructed by dividing weekly revenue by the quantity sold. For weeks in which transactions occur during price discounts, regular unit prices are equal to the last observed regular unit price. Around 9.0% of monthly observations are price discounts.[17]

3.4 Empirical definitions

The micro data used in this paper presents us with two challenges for accurate measurement of price selection: heterogeneity across products, locations and stores, and measurement errors. These

[16]More details are provided in Bronnenberg, Kruger, and Mela (2008).

[17]Coibion, Gorodnichenko, and Hong (2015) use the Symphony IRI dataset to study retail prices and household expenditures across metropolitan areas, finding that reallocation of expenditures across retailers during local recessions lowers average prices paid by consumers.

issues may lead to biased estimates of price moments in the data, such as price selection.[18]

Heterogeneity of price behaviours across products, stores and locations has been well-documented, including not only the differences in the frequency and size of price changes, but also the incidences of price discounts, product churning, and stockouts.[19] To minimize the effect of heterogeneity on average statistics, we first define "elementary" reset and preset price levels for each product category at the level of an elementary price index, stratum (i.e., location and store-type pairing). For each category-stratum preset (reset) price level is defined as the unweighted means of starting (ending) log price levels for all products in the category-stratum in each month. To avoid comparing reset and preset price "dollar" levels across different categories, they are expressed as log deviations from the average for all log prices in the respective category-stratum. We then take weighted averages of reset and preset prices across strata for each category or across all strata and categories to obtain, respectively, category-specific or aggregate reset and preset price levels. Such an approach—treating prices equally within category-strata and weighting them by consumption expenditure weights when aggregating across strata and categories—is very similar to how the statistical agencies construct their CPI's (ILO, 2004).

Taking category-stratum averages helps to correct random coding errors, such as, for example, entering a price of 9.99$ instead of 99.99$. To account for other rare but volatile month-to-month price movements we exclude observations with log-price changes larger in absolute value than the 99th percentile of absolute log price changes within each category-stratum, similar to the treatment in Alvarez, Le Bihan, and Lippi (2016). We also exclude strata with less than 10 price changes over the sample period.

The empirical counterparts of the four variables entering inflation decomposition (4) are constructed as follows. Let p_{isct} denote log price of product i in stratum s and category c in month t, and let P_{sct} denote the elementary price index for stratum s and category c in month t. Index i uniquely identifies an individual product in a particular retail outlet and location. Let ω_{sct} denote expenditure weight corresponding to stratum s and category c in month t, and N_{sct} be the number of observations in stratum s and category c in month t. To control for level- and trend-effects across products, we define month-t log price deviation as the log price level in month t relative to the elementary price level in month $t-1$, $\widehat{p}_{isct} = p_{isct} - P_{sct-1}$, and month-$t$ lagged log price deviation as the price level in month $t-1$ relative to the elementary price level in month $t-1$, $\widehat{p}_{-1,isct} = p_{isct-1} - P_{sct-1}$. Let I_{isct} be an indicator of a price change for product i in month t, $I_{isct} = 1$ if $p_{isct} - p_{isct-1} \neq 0$, and 0 otherwise. Noting that $p_{isct} - p_{isct-1} \equiv I_{isct} \left(p_{isct} - P_{sct-1} + P_{sct-1} - p_{isct-1}\right)$, we can write inflation in stratum s and category c in month t as the weighted mean of log price changes in that

[18] For example, Alvarez, Le Bihan, and Lippi (2016) demonstrate how heterogeneity and measurement errors introduce an upward bias in measured kurtosis of price changes.

[19] Klenow and Malin (2010)and Nakamura and Steinsson (2013) provide detailed reviews of microeconomic evidence on price dynamics and the extent of heterogeneity.

bin and month, and express it identically as follows:

$$\pi_{sct} \equiv \frac{\sum_i (p_{isc,t} - p_{isc,t-1})}{N_{sct}}$$

$$\equiv \underbrace{\frac{\sum_i I_{isc,t}}{N_{sct}}}_{Fr_{sct}} \times \left[\underbrace{\frac{\sum_i I_{isc,t}\widehat{p}_{isct}}{\sum_i I_{isc,t}}}_{P^{res}_{sct}} - \underbrace{\frac{\sum_i I_{isc,t}\widehat{p}_{-1,isct}}{\sum_i I_{isc,t}}}_{P^{pre}_{sct}} \right], \tag{5}$$

which, when aggregated over strata for each category, takes the same form as (4):

$$\pi_{ct} \equiv Fr_{ct} \cdot \underbrace{[P^{res}_{ct} - P^{pre}_{ct}]}_{DP_{ct}}, \tag{6}$$

where $Fr_{ct} = \sum_s \omega_{sct} Fr_{sct}$ is the weighted mean fraction of products in category c changing price in month t; reset price $P^{res}_{ct} = \sum_s \omega_{sct} \frac{Fr_{sct}}{Fr_{ct}} P^{res}_{sct}$ is the weighted mean of prices that changed in month t (relative to category-average price level in month $t-1$); and preset price $P^{pre}_{ct} = \sum_s \omega_{sct} \frac{Fr_{sct}}{Fr_{ct}} P^{pre}_{sct}$ is their corresponding weighted mean level prior to change, in period $t-1$ (relative to category c price level in month $t-1$). Expressions (5) and (6) is the empirical counterpart of inflation decomposition (4): inflation is the product of the fraction of price changes and the difference between reset and preset price levels. Note that the latter can be defined as the weighted-average size of prices that change in month t, $DP_{ct} \equiv P^{res}_{ct} - P^{pre}_{ct}$. Decomposition (6), therefore, nests the breakdown of inflation into extensive and intensive margins (represented by Fr_{ct} and DP_{ct} respectively), proposed by Klenow and Kryvtsov (2008), namely, $\pi_{ct} \equiv Fr_{ct} \cdot DP_{ct}$.

In our empirical analysis in the next section, we assess price selection for category-level time series, using the variables defined in (6). We also repeat the estimation of price selection for aggregate variables, which are constructed as the weighted means of category-level variables: $Fr_t = \sum_c \omega_{ct} Fr_{ct}$, $P^{pre}_t = \sum_c \omega_{ct} \frac{Fr_{ct}}{Fr_t} P^{pre}_{ct}$, and $P^{res}_t = \sum_c \omega_{ct} \frac{Fr_{ct}}{Fr_t} P^{res}_{ct}$, where $\omega_{ct} = \sum_s \omega_{sct}$ are category c consumption-expenditure weights.

The relationship between inflation and "reset price inflation" was studied in Bils, Klenow, and Malin (2012). The define reset price inflation as the estimated rate of change of new prices set by the subset of price changers. Since the subset of price changers varies from month to month, the reset price inflation will depend on both changes in the reset price level as we define above and price selection. Using simulations of the Smets and Wouters (2007) business cycle model, Bils, Klenow, and Malin (2012) show that it is inconsistent with joint dynamics of inflation and reset price inflation in the U.S. data. By offering a direct measure of price selection in the data, our paper helps to better calibrate the features of business cycle models that help them match inflation dynamics, such as price selection and the degree of real rigidities—we return to this point in the next Section.

Table 1 provides descriptive statistics for the U.K., U.S. and Canadian data for the case which excludes price changes due to sales and substitutions.[20] Regular price inflation in the both U.K. and Canada averaged 0.12% and 0.17% per month, or around 1.5% and 2.0% per year, during respective sample periods. In the U.S. grocery data, it was twice as high, at 0.28% per month, or 6.8% per year. In a given month, 12.4% of regular prices change in the U.K., or around once every 8 months. Prices in Canada and grocery prices in the U.S. change 21.7% and 21.3% of time, or once in every 4 months on average. An average magnitude of price changes therefore is 0.92% , 0.83%, and 1.28% in the U.K., Canada, and the U.S, respectively. Reset and preset price levels are expressed as % deviations from the population average, and therefore their averages may vary depending on inflation experiences over the samples in the country datasets. Indeed, both levels are positive for the U.K. (1.39% and 0.46%), negative for the U.S.(–1.07% and –2.35%), and both signs for Canada (0.37% and –0.46%). While our focus is on price selection for variation in inflation, we return to these averages in the context of sticky price models in Section 5. The remaining rows in Table 1 provide the auxiliary statistics that we use for calibrating and evaluating sticky price models.

4 Price selection in the U.K., U.S. and Canadian micro data

4.1 Evidence from product categories

To quantify the degree of price selection at a category level, we estimate the following baseline empirical specification:

$$P_{ct}^{pre} = \beta DP_{ct} + \delta_{cal} + \delta_c + error \tag{7}$$

where the dependent variable, P_{ct}^{pre}, is preset price level for a product category c in month t, and the independent variable of interest is the average size of price changes for category c in month t, DP_{ct}. Since, by definition, $DP_{ct} \equiv P_{ct}^{res} - P_{ct}^{pre}$, the absolute value of the estimated regression coefficient β is equal to the estimated fraction of DP_{ct} variance accounted for by variation in preset price level P_{ct}^{pre} , with the remaining fraction due to reset price level changes. Hence, we adopt the estimated $\hat{\beta}$ as our measure of price selection. By definition, $\hat{\beta}$ is expected to be between −1 and 0, so values of $\hat{\beta}$ that are significantly different (and below) 0 are interpreted as evidence of price selection. Our baseline specification (7) also includes calendar-month fixed effects δ_{cal}, and category fixed effects δ_c. Equation (7) is estimated by a pooled weighted least squares regression.

Table 2 (Panel A) provides the results of this estimation for regular prices, and excluding price changes due to product substitutions. The estimated price selection is –0.385 for the U.K., –0.259 for the U.S., and –0.172 for Canada, all statistically significant at 1% confidence level (row 1 in the Table).[21] While we see a range of values across three countries, we argue below that at least some

[20] Tables A.1–A.3 in Supplementary Material compare descriptive statistics across different treatments of sales and substitutions.

[21] Table A.13 in Supplementary Material provides comparisons with alternative standard errors: Driscoll and Kraay (1998), clustered by category, and clustered by month. The results remain highly significant. Furthermore, including a constant in the regression changes price selection coefficient by about 3%, so it is immaterial for the results below. Table A.14 shows that price selection estimated from the unweighted regressions is very close (around 0.02 difference)

of these differences can be attributed to differences in product coverage and the frequency of price changes. The degree of price selection is little affected by including calendar-month fixed effects, or by adding category-specific linear trends (rows 2 and 3).[22] To visualize price selection, Figure 2 provides scatter plots for nine selected product categories in the U.K., including oil, milk, hotel, and cigarettes. For each category, each point on the plot represents a monthly observation for the average size of price changes (x-axis) and preset price level (y-axis). Hence, each plot represents joint variation of P_{ct}^{pre} and DP_{ct} across months for a given category c. The slope of the trend line is equal to $\hat{\beta}$, representing the estimated degree of price selection. While there is substantial variation in both variables for each category and across categories, they tend to correlate negatively for all categories, pointing to common incidence of price selection.[23]

To rule out price selection as a high-frequency phenomenon, we condition price selection on business cycle frequencies by stripping the regression variables of high and low frequencies using the Baxter-King (12,96,24) bandpass filter. As a result, price selection remains highly statistically significant, although its magnitude is roughly half of the magnitude for monthly series: –0.231 for the U.K., –0.143 for the U.S., and –0.044 for Canada (row 4 in Table 2).

Panel B in Table 2 provides the results for all price changes—both regular and those associated with price discounts. Including price discounts makes price selection at a category level slightly weaker for the U.K. and the U.S., –0.359 and –0.217, respectively; and slightly stronger for Canada, –0.255. Including price changes associated with product substitutions, shown in Tables A.4–A.6 in Supplementary Material makes price selection a bit stronger in the U.K., and slightly weaker in Canada, –0.404 and –0.142; and substitutions are not conducted in the IRI dataset. Hence, price discounts and substitutions do not appear to materially influence price selection at a category level.

We further investigate how much price selection differs across categories. Figure 3 shows the histogram of price selection coefficients estimated individually for each category in the United Kingdom, for the case with regular prices and no substitutions. The empty red bars show the histogram for all estimated coefficients. To focus on the coefficients that are accurately estimated, we also plot the histogram of the coefficients that are statistically different from zero (solid bars). Almost all such coefficients are included in the theoretical range between −1 and 0. The weighted mean across all price selection values (all non-zero values) is –0.355 (–0.444), and the weighted median is lower at –0.356 (–0.527) since the distribution of price selection is somewhat negatively skewed.

How much does the level of aggregation matter for price selection? We repeat the estimation for two alternative levels of aggregation used for computing the variables in (7). At a finer level, we compute the variables by category-stratum, i.e., at the level for which goods and services differ not

to the point estimates from the weighted regressions.

[22]We also experimented taking out stochastic trends at a category-stratum level—price selection is stronger by about a third.

[23]Variation in the average size of price changes, DP_{ct}, accounts for most of the variation in inflation, as pointed out by Klenow and Kryvtsov (2008)—71% for the U.K. at a category level. Hence, if we regress P_{ct}^{pre} (multiplied by the mean fraction of price changes Fr_c) on inflation π_{ct}, instead of the average size of price changes DP_{ct}, the estimated coefficients remain significant and negative (–0.118 for the U.K).

only by their physical characteristics, but also by geographical location and store type (less or more than 10 outlets); at this level statistical agencies define elementary price indices treating all price observations with equal weights. In the U.K. data, this increases the size of cross-section by a factor of 24. At a coarser level, we compute the variables by COICOP class, decreasing the cross-section by a factor of 16. To handle a large number of fixed effects at a category-stratum level, we estimate (7) only for food products, which are captured in 298 categories, or around 28% of all categories in the basket, see Table 3. At a category level, price selection for food is somewhat weaker than for all categories, –0.269 versus –0.385, for regular prices and no substitutions. Note that this estimate is much closer to –0.259 obtained using the Symphony IRI dataset for the U.S., which covers grocery items. At a finer, category-stratum level price selection for food in the U.K. is stronger by about a third, –0.359 versus –0.269. In turn, at a coarser, class level selection is weaker by about 42%, –0.156 versus –0.269. Hence, price selection weakens with aggregation. This finding is robust when price discounts or product substitutions are included. This evidence is unaccounted for by standard one-sector sticky price models; and, as we argue in Section 5, it provides guidance for research with multi-sector models.

4.2 Evidence from aggregate time series

We then study the degree of price selection at the *aggregate* level. The regression of preset price level on the average size of price changes is applied to these aggregate variables:

$$P_t^{pre} = \beta DP_t + \delta_{cal} + error \tag{8}$$

where as before δ_{cal} denotes calendar-month fixed effects.

Panel A in Table 4 provides the results of this estimation for regular prices. We find that for aggregate time series price selection is substantially weakened for regular prices: –0.198 for the U.K., and it is not significantly different from zero for the U.S. and Canada. Similar to the category-level evidence, including substitutions does not change price selection at the aggregate level.

By contrast, when regression variables are constructed using all prices—both regular and sales prices—substantial degree of price selection remains at the aggregate level for the U.K. and U.S., as shown in Panel B of Table 4: –0.394 for the U.K. and –0.140 for the U.S., which is close in magnitude to price selection at the category level. Hence, while aggregation of category-level regular price changes largely washes out price selection, the opposite happens when price discounts are included. This suggests that price discounts represent an important margin of price adjustment in response to aggregate shocks. This finding is consistent with Kryvtsov and Vincent (2017) who use evidence from the U.K. and U.S. CPI micro data and find that the incidence of price discounts is strongly countercyclical, amplifying fluctuations in the price of aggregate consumption. In Canada, aggregate price selection is zero for either regular or all posted prices, consistent with less cyclicality in sales behaviour.

4.3 Price selection and price adjustment

How does price selection vary with price behaviour? We explore the richness of the datasets at hand to answer this question and provide more guidance for business cycle models, discussed in Section 5. We modify the panel regression (7) by allowing price selection to vary with price adjustment moments, so that $\beta = \beta_1 + \beta_2\Gamma_{ct}$, where Γ_{ct} is one of price adjustment moments for category c in month t. in two ways. We also focus on cross-section variation since it is larger than variation across time, thus giving us a better chance of detecting the relationship between price selection and price adjustment. This leads us to the following empirical specification:

$$P_{ct}^{pre} = \beta_1 DP_{ct} + \beta_2 DP_{ct} \times \Gamma_{ct} + \delta_t + error \tag{9}$$

where $DP_{ct} \times \Gamma_{ct}$ are the interaction terms between DP_{ct} and Γ_{ct}, and δ_t and month fixed effects. For the interaction terms, we consider five price adjustment moments: the frequency and average size of price changes, Fr_{ct} and DP_{ct}, the average absolute size of individual price changes, kurtosis of non-zero price changes, and standard deviation of complete price spells. The last two moments are first computed for each category and stratum, and then averaged across strata using weighted means.

Table 5 provides estimation results for regular prices and no substitutions. Without interaction terms (column A), price selection across section is consistent with price selection stemming from variation across time, reported above: –0.317 for the U.K., –0.256 for the U.S., and –0.204 for Canada, all highly statistically significant. We visualize our cross-section findings in Figure 4, which provides scatter plots for nine selected months in the U.K. for all prices and excluding substitutinos. For each month, each point on the plot represents a observation for a particular product category, giving the average size of price changes (x-axis) and preset price level (y-axis). The size of each point represents that category's consumption weight. Hence, each plot represents joint variation of P_{ct}^{pre} and DP_{ct} across categories in given month. The slope of the trend line is equal to $\hat{\beta}$, representing the estimated degree of price selection. Similar to the case for time variation, there is substantial variation in both variables across categories in a given month, but they tend to correlate negatively for all months, pointing to common incidence of price selection across section.

Column B in Table 5 provides the results for full specification (9), which includes all five interaction terms. Tables A.7 and A.8 in Supplementary Material contain estimation results for (9) where we add interaction terms one-by-one, and Tables A.9–A.11 in Supplementary Material provide the results for alternative treatments of observations with price discounts and product substitutions. We look for the results that are robust across all specifications and across all three datasets.

First, we find that price selection is stronger for categories where price changes are less frequent or larger in absolute magnitude, given by the estimated elasticities $\hat{\beta}_2$ for the interaction terms $DP_{ct} \times Fr_{ct}$ and $DP_{ct} \times ADP_{ct}$. These estimates imply that a 10 percentage point decrease in the fraction of price changes strengthens price selection from –0.317 to –0.356 for the U.K., from –0.256 to –0.310 for the U.S., and from –0.204 to –0.280 for Canada. And a 10 percentage point increase in the absolute magnitude of price changes, strengthens price selection from –0.317 to –0.337 for the U.K., from –0.256 to –0.336 for the U.S., although it weakens in for Canada, from –0.204 to –0.154. Note that higher frequency of price changes in Canada relative to the U.K. (21.7% versus 12.4% on average) may account for somewhat weaker price selection in Canada.[24] This evidence is consistent with intuition for price selection: less frequent price changes or larger idiosyncratic shocks imply that a larger fraction of prices is misaligned relative to the desired level, and therefore in response to a shock of the same magnitude, a larger mass of prices will move closer to the desired price. For example, in Taylor (1980) model price selection accounts for the fraction $\frac{T-1}{2T}$ of inflation variance, where T is the duration of price contracts, i.e., price selection strengthens with price stickiness. This evidence is also corroborated by comparing price selection across the types of product. As reported in Supplementary Material (Table A.12), Services (the lowest frequency of price changes) and Semi-durables (the largest absolute size of price changes) have the first and second strongest price selection; and Non-durables (the highest frequency of price changes) feature the weakest price selection.

Second, price selection is stronger in months in which the average price change is higher, given by $\hat{\beta}_2$ for the interaction term $DP_{ct} \times DP_{ct}$. If the average size if higher by 5 percentage points, price selection strengthens from –0.317 to –0.343 for the U.K., from –0.256 to –0.261 for the U.S., and from –0.204 to -0.229 for Canada. This finding implies that price selection amplifies fluctuations in inflation. We show in the next section that this prediction is born out in non-linear menu cost models.

Finally, we do not find a robust relationship between price selection and kurtosis of non-zero price changes or standard deviation of price spell durations. Hence, our findings do not appear to support the use of these moments as sufficient statistics for the size of monetary neutrality, proposed by Alvarez, Le Bihan, and Lippi (2016) and Carvalho and Schwartzman (2015). We provide some discussion for future work using the sufficient statistic approach in the next section.

5 Price selection in sticky price models

In this section we compare predictions of standard sticky price models with the facts presented in the previous section. In particular, we study price dynamics in Taylor (1980), Calvo (1983), and Golosov and Lucas (2007) models, and the models that nest them. For each model we simulate equilibrium paths of inflation, number of adjusting prices, their average size, and reset and preset price levels. We decompose inflation dynamics into its components due to reset and preset price dynamics and compare it to empirical decomposition in the previous section. We show that price selection varies substantially across models. Model details are provided in Section B of the Supplementary Material.

Each model represents an economy populated by a large number of infinitely lived households and monopolistically competitive producers of intermediate goods. The shocks in this economy

[24] Using the elasticities for the effect of the frequency of price changes on price selection from the U.K. and Canada (0.386 for the U.K., 0.756 for Canada, see Table 5), we estimate that the difference in frequencies of price changes can account for between one and two thirds of the difference in price selection.

are aggregate shocks to the money supply and idiosyncratic productivity shocks. The idiosyncratic shocks follow an AR(1) process normally distributed i.i.d. innovations, and money supply follows random walk with drift, also with normally distributed i.i.d. innovations.

Each model is parameterized to match three moments regarding micro-level price behaviour: the average fraction of price changes in a given month, their average absolute size, and serial correlation of newly adjusted prices. For concreteness, we use the moments for the U.K. reported in Table 1, but we note that the takeaways we develop in this Section are not sensitive to which combination of moments we use. In the U.K. data, we use regular price changes (excluding substitutions) to compute the weighted mean fraction and absolute size of price changes; their across-time means are 0.124 and 12.2%, respectively. To compute serial correlation of adjusted prices, we compute a linear trend for each regular price quote line and express prices in terms of percent deviations from the trend. For each month, we then compute a weighted AR(1) correlation coefficient between such prices across months in which they changed. The mean correlation across months is –0.03. We also pick the size of the monetary shocks to match the standard deviation of regular-price inflation in the data, 0.23%.

The remaining parameters are assigned as follows: the discount factor is $0.96^{1/12}$, corresponding to a 4% annualized average real rate of interest. Mean rate of the money growth is 0.12 to have the model match the mean rate of regular price inflation of 0.12, or 1.5% per year.

The demand for product varieties is derived under assumptions of constant elasticity of substitution between consumption goods, which we choose to equal to 3, in line with studies of retail price behaviour (Midrigan, 2011), and strategic neutrality of pricing decisions, as usually assumed in menu cost models (Golosov and Lucas, 2007).[25]

We confront sticky price models with our findings for the dynamics of inflation and its components. To compute the moments, we simulate equilibrium dynamics in each model over 235 months for a given draw of a money growth shocks and 10000 draws of idiosyncratic productivity shock.[26] For each simulation we compute the time series for each of the components of the inflation decomposition given by (6) and the model counterparts of the empirical moments reported in Table 2. All moments are computed by applying the same definitions as in Section 3.4 to the artificial model-generated data. We repeat this simulation 100 times and report the means and standard deviations of model moments over these simulations in Table 7.

We find significant differences in the degree of price selection across the models (Panel B in Table 7). In the Calvo model price selection is close to zero,[27] since the timing of price changes is independent of the state of the economy. By contrast, in Golosov-Lucas and Taylor models price selection is significant, –0.34 and –0.44, respectively. Hence, in accordance with Golosov and Lucas (2007) and Carvalho and Schwartzman (2015) we document strong price selection in these two

[25] In the accompanying paper (Carvalho and Kryvtsov, 2017), we explore the implication of both price selection and real rigidities for the degree of monetary non-neutrality in these models.

[26] We simulate the dynamics for 255 months and discount the first 20 months to remove the effect of initial conditions.

[27] In the Calvo model there is a small negative correlation between the average size of price changes and reset price level. This is because in months following the monetary impulse, the gradual decrease in the average size of price changes is associated with steady increase in the reset price level.

models.

Evidently, price selection in standard sticky price models are on the opposite extremes of the range of values we find in the data, reported in Tables 2 and 4. Calvo model is in line with zero selection at the aggregate level for the U.S. and Canada, although not for the U.K. where aggregate price selection is –0.153 or stronger. Golosov-Lucas and Taylor models are consistent with price selection at a category level for the U.K.. They predict stronger price selection than in the U.S. and Canada, although some of these differences can be due higher frequencies of price changes in the U.S. and Canada than what we used for model calibration.

Clearly, none of these one-sector models can match both strong selection at a sector level and weak selection at the aggregate level. This creates a challenge for assessing the degree of inflation-output trade-off because these models' predictions about the trade-off are closely linked to the degree of price selection. For example, Panel C in Table 7 shows that the degree of monetary non-neutrality in Calvo model, measured by the half-life of consumption impulse responses to +1% impulse to money growth, is larger than in Golosov-Lucas (Taylor) model by a factor of 4.6 (1.6).

Our analytical results suggest that multi-sector models based on Golosov-Lucas or Taylor price adjustment may be more successful in matching price selection at both aggregate and sector levels. At a sector level we already established that state-dependent or Taylor can generate strong price selection observed at that level in the micro data. At the aggregate level, price selection in the multi-sector model weakens due to two distinct mechanisms.

First, higher frequency of price changes weakens price selection. In Section C.3 of Supplementary Material we show that price selection in a plain-vanilla Taylor model with price duration T is equal to $-\frac{T-1}{2T}$. In Taylor model, the oldest prices tend to be those that are most misaligned and so their adjustment is associated with price selection. The larger price stickiness (large T) the stronger price selection.[28] Hence, sectors with more flexible prices may contribute to weaker price selection at the aggregate level.

Second, aggregation in itself weakens selection. In Section C.4 of Supplementary Material we provide a simple analytical example in simple Taylor model with two sectors with price durations $T_1 = 2$ and $T_2 = 4$. Sector level price selection coefficients in this case are equal to $-\frac{1}{4}$ and $-\frac{3}{8}$, respectively. It turns out that aggregate price selection is $-\frac{11}{40}$, which is weaker than the average price selection $-\frac{5}{16}$. As explained in Kara (2015) and Carvalho and Schwartzman, 2015, additional weakening of price selection is due to the fact price adjustments in a flexible sector are over-represented among all price changes. In our example, in any period two thirds of all price changes are in sector 1 even though both sectors are equally weighted in the price index. Since price selection associated with these price changes is weaker, the aggregate selection is weaker than the average.

Our findings are complimentary to the "sufficient statistic" approach in this literature that explores the theoretical mapping between particular moments in the price data and the size of monetary non-neutrality. According to this approach, conditional on matching the sufficient statis-

[28] Price selection in time-dependent pricing models are more generally studied in Carvalho and Schwartzman, 2015.

tic—assumed to be available in the micro data—sticky price models provide an accurate prediction for the size of monetary non-neutrality, regardless of the mechanisms behind it. The two most recently proposed sufficient statistics are based on the kurtosis of price changes (Alvarez, Le Bihan, and Lippi, 2016) and the standard deviation of price spell durations (Carvalho and Schwartzman, 2015). Unlike the sufficient-statistic approach that relies on theory, we provide a direct measure of one of the mechanisms linking micro moments with monetary non-neutrality. Evidence from cross-section regressions in Section 4.3 provides only mixed support for the relationship between price selection and either of the two sufficient statistics. We hypothesize that combining our measure of price selection with the sufficient statistics approach may help to assess the importance of other drivers of monetary non-neutrality, such as real rigidities.[29]

6 Conclusions

We propose a new decomposition of monthly inflation into components varying with the number of individual prices that change, and with their levels before and after the change, which we call a *reset* and a *preset* price components. We use the decomposition to learn about inflation dynamics and assess different models of price setting. To that end, we apply our decomposition to U.K., U.S. and Canadian CPI inflation, using its underlying micro price data. We find that at a product category level the average level from which prices adjust is negatively correlated with inflation, accounting for around 39% of its variance in the United Kingdom, 26% in the United States, and 17% in Canada. Aggregation largely washes out price selection for regular price changes, but not for changes associated with price discounts. Price selection is stronger for categories where price changes are less frequent, larger in absolute magnitude, or in months with larger inflation deviations.

We then apply our decomposition to to artificial micro data generated by calibrated versions of Taylor (1980), Calvo (1983), and Golosov and Lucas (2007) models of price setting. We find that price selection in standard sticky price models are on the opposite extremes of the range of values we find in the data, and none of these one-sector models can match both strong selection at a sector level and weak selection at the aggregate level. Our analytical results suggest that multi-sector sticky price models with strong price selection at a sector level may be more successful in matching price selection at both aggregate and sector levels.

Standard models have predominantly relied on Calvo nominal price adjustment and real rigidities to account for business cycles and the flat Phillips Curve. Our results suggest that a significant share of inflation volatility may be unaccounted for by these models, leading them to predict a flatter Phillips Curve. By construction, our measure of price selection takes inflation as given, and therefore, this method abstracts from the shocks driving inflation dynamics or the mechanisms that relate inflation fluctuations to changes in real activity, such as real rigidities. Future research should study these mechanisms and shocks jointly with price selection and draw implications for business cycles and the inflation-output trade-off.

[29] In the accompanying paper (Carvalho and Kryvtsov, 2017), we explore the implication of both price selection and real rigidities for the degree of monetary non-neutrality in sticky price models.

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Table 1: Descriptive statistics

	Statistic	U.K.	Canada	U.S.
	Consumption coverage	Non-shelter goods and services	Non-shelter goods and services	Grocery products
	Sample	1996:02 - 2015:09	1998:02 - 2009:12	2001:01 - 2011:12
	# of months	236	143	132
	# of obs/month	102,801	58,670	274,369
	# of categories	1152	705	31
(1)	π	0.121	0.171	0.282
(2)	Fr	0.124	0.217	0.213
(3)	DP	0.924	0.832	1.281
(4)	P^{pre}	1.387	0.370	-1.066
(5)	P^{pre}	0.463	-0.462	-2.347
(6)	adp	12.16	8.14	8.32
(7)	corr	-0.033	0.165	-0.028
(8)	sd_delta	15.65	9.88	10.90
(9)	kurt	5.73	4.72	4.96
(10)	meandur	5.65	6.85	3.47
(11)	sd_dur	5.33	6.21	3.95
(12)	frac of sales	5.6	9.0	9.0
(13)	frac of subs	4.6	3.5	N/A

Notes: Data are from the U.K. Office for National Statistics CPI database, available at http://www.ons.gov.uk/ons/datasets-and-tables/index.html, the Statistics Canada's Consumer Price Research Database, and the Symphony IRI Inc.. Sample period: [UK]: from February 1996 through September 2015; [Canada]: from February 1998 to December 2009; [U.S.]: from January 2001 to December 2011.

The entries are means across time of the monthly values of each variable. The monthly values of the variables are across-product weighted means with weights based on consumption expenditures. For computing statistics in rows (1)-(11), price changes due to sales or substitutions are excluded (Tables 1-3 in Supplementary Material provide statistics for other cases). p - inflation, in %; Fr - the fraction of items with changing prices; DP - the size of price changes, in %; Ppre (Pres) - preset (reset) price level defined as the unweighted means of starting (ending) log price levels for all products in the category-stratum in each month, expressed as % deviations from the average for all log prices in the respective category-stratum; adp - the average absolute size of price changes, in %; corr - serial correlation of newly set prices for an individual product; sd_delta - standard deviation of non-zero price changes for a given category-stratum, in %; kurt - kurtosis of non-zero price changes for a given stratum; meandur - mean price spell duration (for complete spells), in months; sd_dur - standard deviation of price spell durations for a given stratum (for complete spells), in months; frac of sales - fractions of observations with discounted price; mean frac of subs - mean fraction of observations with product substitutions.

Table 2: Price selection, category time series

Sample	U.K.	Canada	U.S.
	A. Regular prices		
(1) Excl. seasonal effects	-0.385***	-0.172***	-0.259***
	(0.006)	(0.011)	(0.001)
(2) Incl. seasonal effects	-0.384***	-0.168***	-0.256***
	(0.006)	(0.011)	(0.001)
(3) Linear trend	-0.373***	-0.184***	-0.254***
	(0.006)	(0.011)	(0.001)
(4) Bandpass filtered	-0.231***	-0.044***	-0.143***
	(0.017)	(0.013)	(0.003)
Number of obs for (1)	115,776	49,545	390,620
R^2 for (1)	0.108	0.158	0.278
	B. All posted prices		
(5) Excl. seasonal effects	-0.359***	-0.255***	-0.217***
	(0.005)	(0.004)	(0.001)
(6) Incl. seasonal effects	-0.360***	-0.252***	-0.215***
	(0.005)	(0.004)	(0.001)
(7) Linear trend	-0.341***	-0.254***	-0.211***
	(0.005)	(0.004)	(0.001)
(8) Bandpass filtered	-0.269***	-0.122***	-0.147***
	(0.015)	(0.013)	(0.003)
Number of obs for (5)	116,312	54,129	410,387
R^2 for (5)	0.176	0.253	0.362

Notes: Data sources are described in notes for Table 1. Price changes due to sales or substitutions are excluded. The entries are the estimated values of the coefficient in the weighted panel regression (7) of preset price level on the average size of price changes, with variation across product categories and across months. Panel regression includes calendar-month fixed effects and category fixed effects. Panel A provides estimates for the sample excluding price discounts and product substitutions. Panel B uses all prices and excludes substitutions. Standard errors are in parentheses. *** -- denotes statistical significance at 1% confidence level, ** -- 5% level, and * -- 10% level. Rows (1) and (5) denote benchmark case, rows (2) and (6) do not control for calendar fixed effects, rows (3) and (7) add category-specific linear trends in the regression, rows (4) and (8) denote cases where preset and reset prices are detrended by Baxter-King (12, 96, 24) bandpass filter at category level.

Table 3: Price selection by level of aggregation, for food products in the United Kingdom

	Level of aggregation	Number of cross-section categories	Regular prices, excl. substitutions	Regular prices, incl. substitutions	Posted prices, excl. substitutions	Posted prices, incl. substitutions
(1)	Category and stratum	7079	-0.359***	-0.370***	-0.364***	-0.365***
			(0.002)	(0.002)	(0.002)	(0.002)
(2)	**Category**	**298**	**-0.269*****	**-0.302*****	**-0.290*****	**-0.297*****
			(0.007)	**(0.006)**	**(0.005)**	**(0.005)**
(3)	Basic class	13	-0.156***	-0.156***	-0.186***	-0.182***
			(0.018)	(0.016)	(0.013)	(0.013)

Notes: Data are from the U.K. Office for National Statistics CPI database, available at http://www.ons.gov.uk/ons/datasets-and-tables/index.html. Sample period is from February 1996 through September 2015. The entries are coefficient in the regression of preset price level on the average size of price changes. Levels of aggregation: category corresponds to "representative item"; category-stratum adds variation across geographical location and store type (less or more than 10 outlets); basic class is defined by Classification of Individual Consumption by Purpose (COICOP). Panel A provides coefficients in the weighted panel regression (7), with variation across product categories and across months. Panel regression also includes calendar-month fixed effects and category fixed effects. Standard errors are in parentheses. *** -- denotes statistical significance at 1% confidence level, ** -- 5% level, and * -- 10% level.

Table 4: Price selection, aggregate time series

Sample	U.K.	Canada	U.S.
	A. Regular prices		
(1) Excl. seasonal effects	-0.198***	-0.011	0.060*
	(0.072)	(0.018)	(0.035)
(2) Incl. seasonal effects	-0.153**	0.001	-0.018
	(0.067)	(0.018)	(0.026)
(3) Linear trend	-0.227***	-0.004	0.062
	(0.071)	(0.018)	(0.035)
(4) Bandpass filtered	-0.319***	0.078	0.207***
	(0.109)	(0.101)	(0.035)
Number of obs for (1)	235	133	131
R^2 for (1)	0.110	0.285	0.132
	B. All posted prices		
(5) Excl. seasonal effects	-0.394***	-0.041	-0.140***
	(0.065)	(0.027)	(0.021)
(6) Incl. seasonal effects	-0.378***	-0.016	-0.134***
	(0.043)	(0.026)	(0.019)
(7) Linear trend	-0.308***	-0.027	-0.141***
	(0.063)	(0.025)	(0.017)
(8) Bandpass filtered	-0.293***	-0.043	0.254***
	(0.112)	(0.114)	(0.049)
Number of obs for (5)	235	133	131
R^2 for (5)	0.327	0.330	0.325

Notes: Data sources are described in notes for Table 1. Price changes due to substitutions are excluded. The entries are the estimated values of the coefficients in time-series regression (8), with variation across months; it also includes calendar-month fixed effects. Panel A provides estimates for the sample excluding price discounts and product substitutions. Panel B uses all prices and excludes substitutions. Standard errors are in parentheses. *** -- denotes statistical significance at 1% confidence level, ** -- 5% level, and * -- 10% level. Rows (1) and (5) denote benchmark case, rows (2) and (6) do not control for calendar fixed effects, rows (3) and (7) add category-specific linear trends in the regression, rows (4) and (8) denote cases where preset and reset prices are detrended by Baxter-King (12, 96, 24) bandpass filter at item (Panel A) and aggregate (Panel B) levels.

Table 5: Price selection and price changes across product categories, regular prices

Independent variables	U.K.		Canada		U.S.	
	(A)	(B)	(A)	(B)	(A)	(B)
DP	-0.317***	-0.257***	-0.204***	-0.797***	-0.256***	-0.300***
	(0.006)	(0.039)	(0.011)	(0.062)	(0.001)	(0.005)
<u>Interaction terms</u>						
DP x Fr		0.386***		0.756***		0.643***
		(0.048)		(0.046)		(0.007)
DP x ADP		-0.002**		0.006***		-0.008***
		(0.001)		(0.002)		(0.000)
DP x Kurt p-changes		-0.019***		0.025***		-0.000
		(0.004)		(0.009)		(0.000)
DP x Std p-spells		0.004		0.036***		0.000
		(0.003)		(0.003)		(0.001)
DP x DP		-0.005***		-0.003***		-0.001***
		(0.000)		(0.001)		(0.000)
Number of obs	115,776	115,772	49,545	49,538	390,620	390,607
R^2	0.034	0.0413	0.010	0.016	0.110	0.139

Notes: Data sources are described in notes for Table 1. Price changes due to sales or substitutions are excluded. The entries are coefficients in the weighted panel regression (9), with variation across product categories. Panel regression also includes month fixed effects. Column (A) provides price selection coefficient in the regression without fixed effects. Column (B) breaks down price selection via interaction with category-level means: Fr -- mean fraction of price changes, ADP -- mean absolute size of price changes, Kurt -- mean kurtosis of non-zero price changes at stratum level, Std p-spells -- mean of the standard deviation of complete price spell durations at stratum level, DP -- mean average size of price changes. Standard errors are in parentheses. *** -- denotes statistical significance at 1% confidence level, ** -- 5% level, and * -- 10% level.

Table 6: Price selection and price changes across product categories, all prices

Independent variables	U.K.		Canada		U.S.	
	(A)	(B)	(A)	(B)	(A)	(B)
DP	-0.304***	-0.224***	-0.242***	-0.656***	-0.207***	-0.314***
	(0.005)	(0.032)	(0.005)	(0.034)	(0.001)	(0.004)
Interaction terms						
DP x Fr		0.167***		0.503***		0.414***
		(0.034)		(0.024)		(0.005)
DP x ADP		-0.001		0.002**		-0.004***
		(0.001)		(0.001)		(0.000)
DP x Kurt p-changes		-0.021***		0.050***		0.008***
		(0.003)		(0.005)		(0.000)
DP x Std p-spells		-0.007***		0.016***		0.000
		(0.003)		(0.002)		(0.000)
DP x DP		-0.003***		-0.004***		-0.002***
		(0.000)		(0.000)		(0.000)
Number of obs	116,312	116,312	54,129	54,129	410,387	410,377
R^2	0.045	0.050	0.048	0.070	0.137	0.175

Notes: Data sources are described in notes for Table 1. Price changes due to substitutions are excluded. The entries are coefficients in the weighted panel regression (9), with variation across product categories. Panel regression also includes month fixed effects. Column (A) provides price selection coefficient in the regression without fixed effects. Column (B) breaks down price selection via interaction with category-level means: Fr -- mean fraction of price changes, ADP -- mean absolute size of price changes, Kurt -- mean kurtosis of non-zero price changes at stratum level, Std p-spells -- mean of the standard deviation of complete price spell durations at stratum level, DP -- mean average size of price changes. Standard errors are in parentheses. *** -- denotes statistical significance at 1% confidence level, ** -- 5% level, and * -- 10% level.

Table 7: Price selection in sticky price models

	Data	Calvo	Taylor	GL
A. Calibration targets				
Fraction of pch, %	0.12	0.125	0.125	0.121
		(0.000)	(0.000)	(0.000)
Abs size of pch, %	12.2	12.4	12.3	12.2
		(0.1)	(0.0)	(0.1)
Serr corr of reset prices	-0.03	-0.03	-0.03	-0.05
		(0.05)	(0.02)	(0.02)
Inflation mean, %	0.12	0.12	0.14	0.12
		(0.06)	(0.06)	(0.02)
Inflation stdev, %	0.23	0.23	0.23	0.23
		(0.03)	(0.03)	(0.01)
B. Price selection	**-0.14**	**-0.01**	**-0.44**	**-0.34**
		(0.01)	(0.01)	(0.01)
C. Predicted moments				
Consumption stdev, %		1.60	0.98	1.27
		(0.20)	(0.10)	(0.02)
Consumption ser. corr		0.86	0.79	0.84
		(0.04)	(0.04)	(0.06)
Half-life of C, months		4.88	2.96	1.07
		(3.54, 6.31)	(2.40, 3.51)	(0.90, 1.28)
Std of price spells	5.3	7.21	0.00	7.92
		(0.08)	(0.00)	(0.07)
Kurtosis of p-changes	5.7	4.79	3.00	1.23
		(0.02)	(0.00)	(0.02)

Notes: Table provides the results from simulations of three models: Calvo (1983), Taylor (1980), Golosov and Lucas (2007). We simulate equilibrium dynamics in each model over 235 months for a given draw of a money growth shocks and 10000 draws of idiosyncratic productivity shock. For each simulation we compute the time series for each of the variables. We repeat this simulation 100 times and report the means and standard deviations of model moments over these simulations.

Figure 1: Price selection in sticky price models

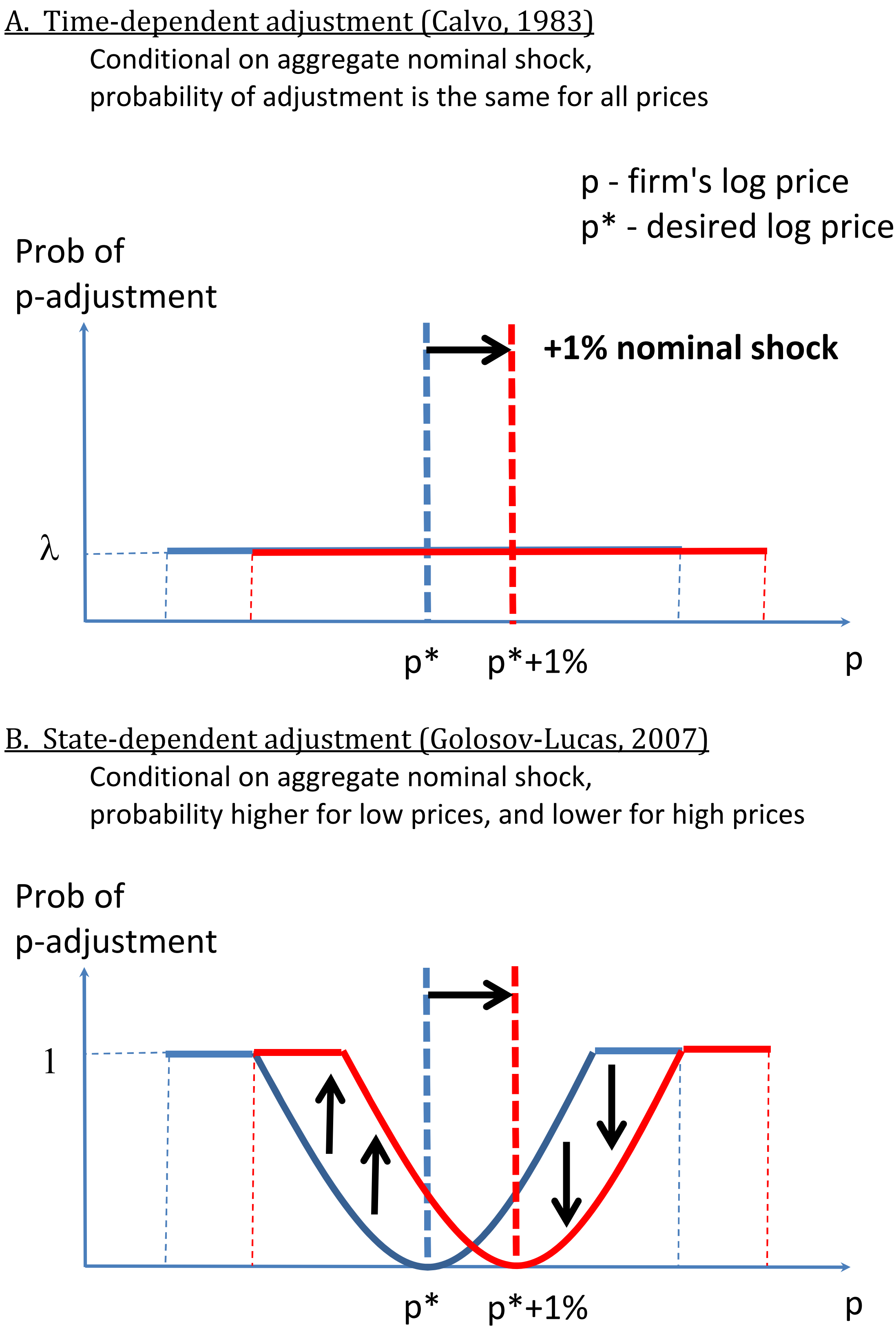
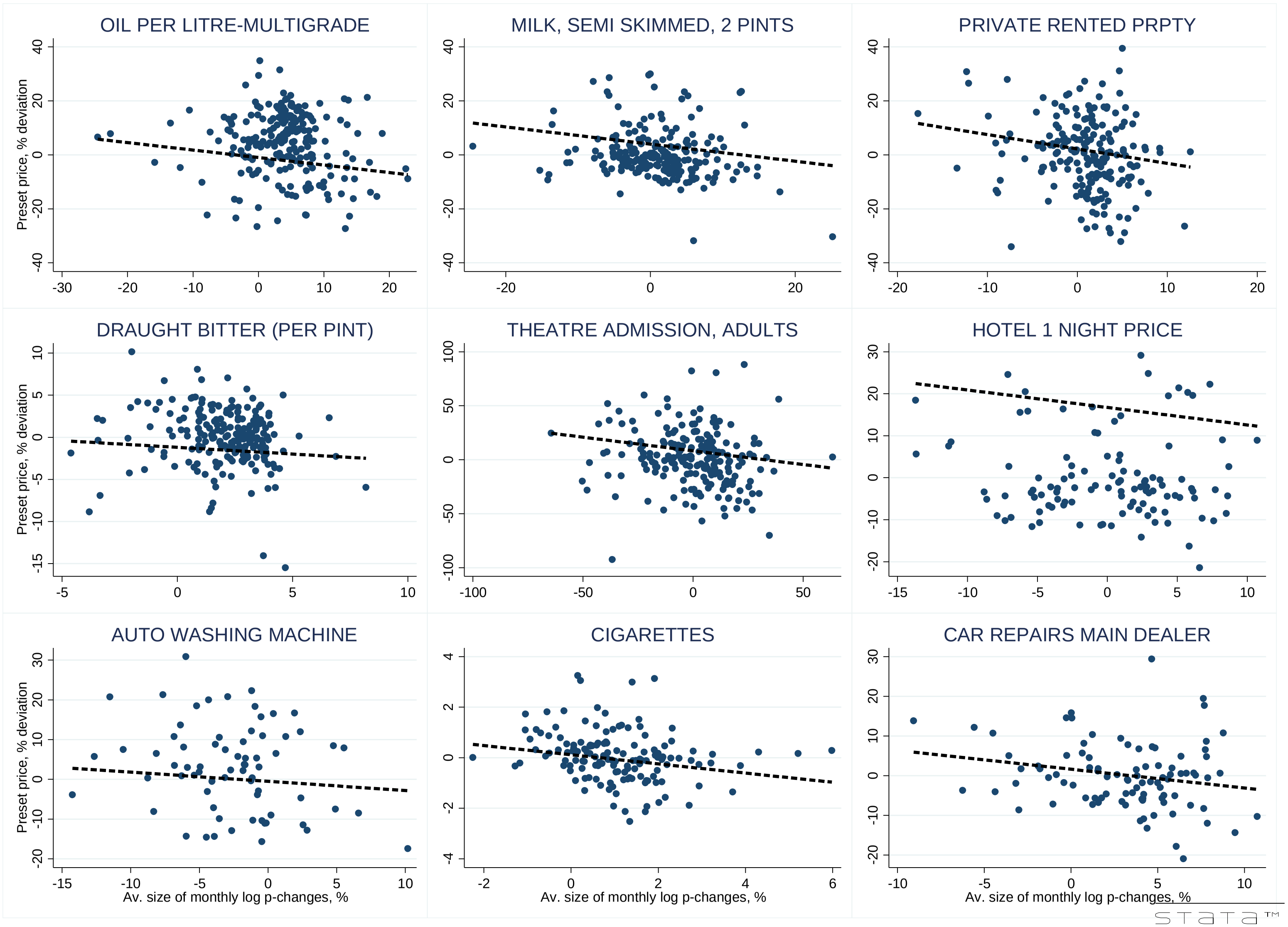


Figure 2: Preset price level and average size of price changes, variation over time for selected product categories, U.K. CPI data



Notes: Figure provides scatter plots for nine selected product categories in the U.K., including oil, milk, hotel, and cigarettes. For each category, each point on the plot represents a monthly observation for the average size of price changes (x-axis) and preset price level (y-axis). Hence, each plot represents joint variation of P_{ct}^{pre} and DP_{ct} across months for a given category c. The slope of the trend line is equal to $\hat{\beta}$, representing the estimated degree of price selection.

Figure 3: Price selection across product categories, U.K. CPI data

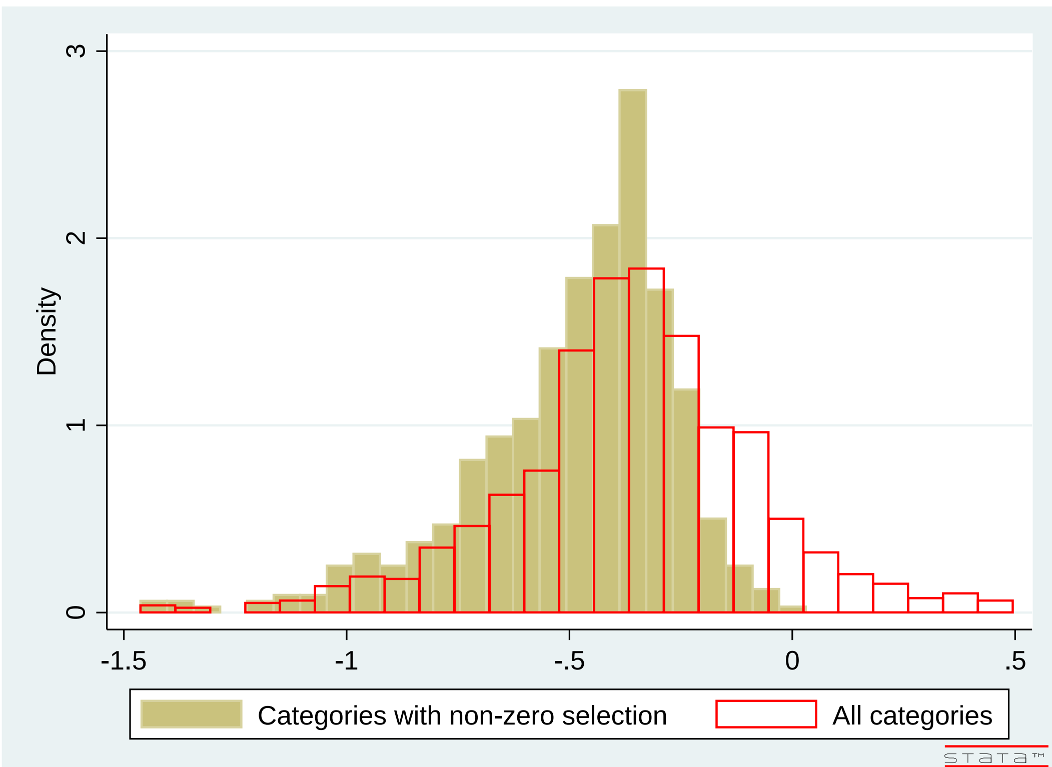
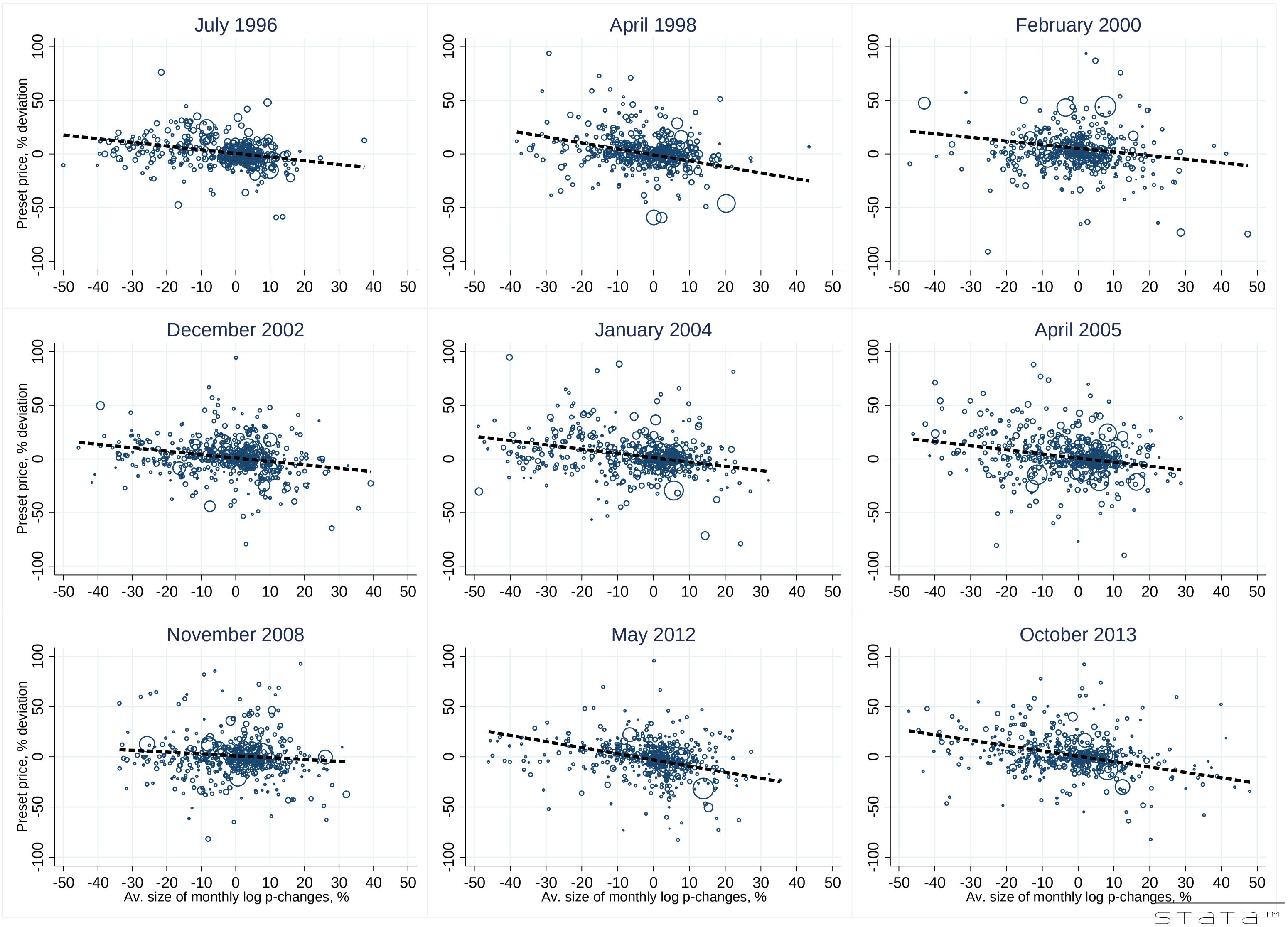


Figure shows the histogram of price selection coefficients estimated individually by estimating regression (8) for each category in the United Kingdom, for the case with regular prices and no substitutions. The empty red bars show the histogram for all estimated coefficients. Solid bars show the coefficients that are statistically different from zero.

Figure 4: Preset price level and average size of price changes, variation over product categories for selected months, U.K. CPI data



Notes: Figure provides scatter plots for nine selected months in the U.K. for all prices and excluding substitutinos. For each month, each point on the plot represents a observation for a particular product category, giving the average size of price changes (x-axis) and preset price level (y-axis). The size of each point represents that category's consumption weight. Hence, each plot represents joint variation of P_{ct}^{pre} and DP_{ct} across categories in given month. The slope of the trend line is equal to $\hat{\beta}$, representing the estimated degree of price selection.